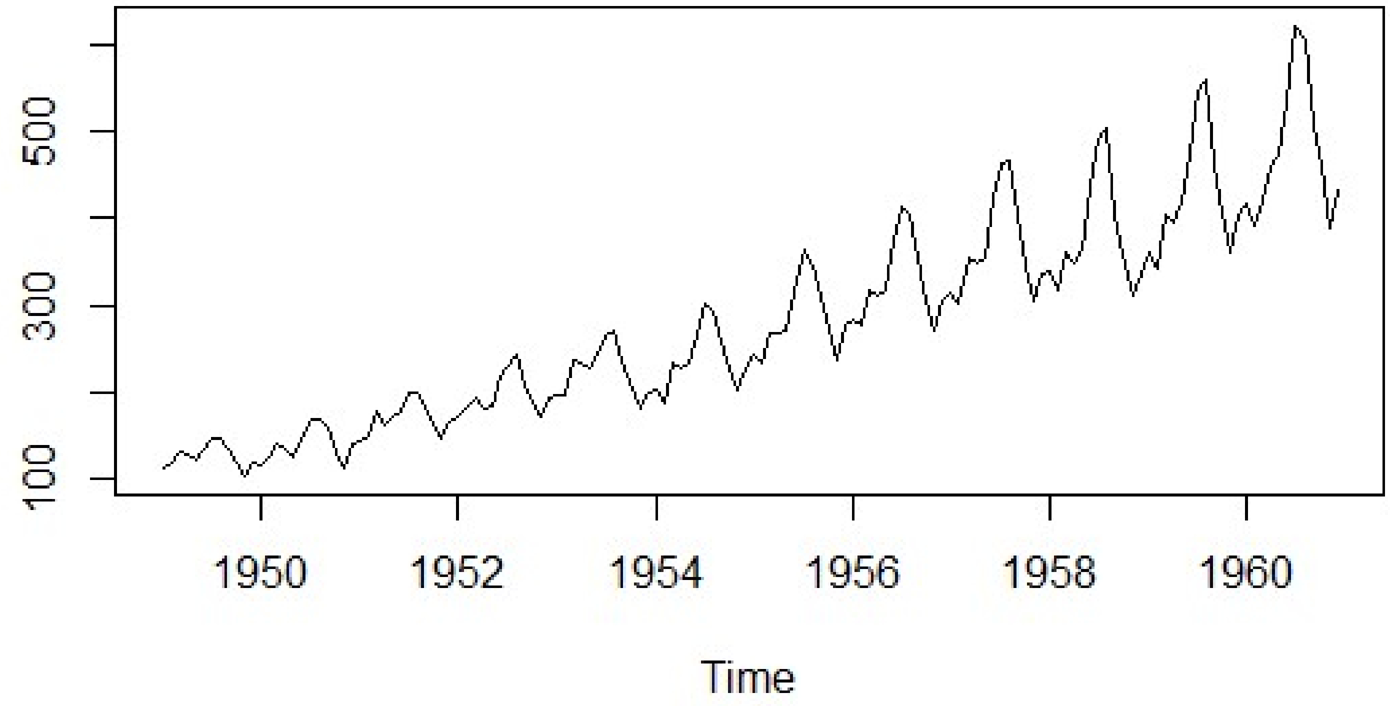
Introduction to Time Series Analysis

Hotel Seasonal Problem

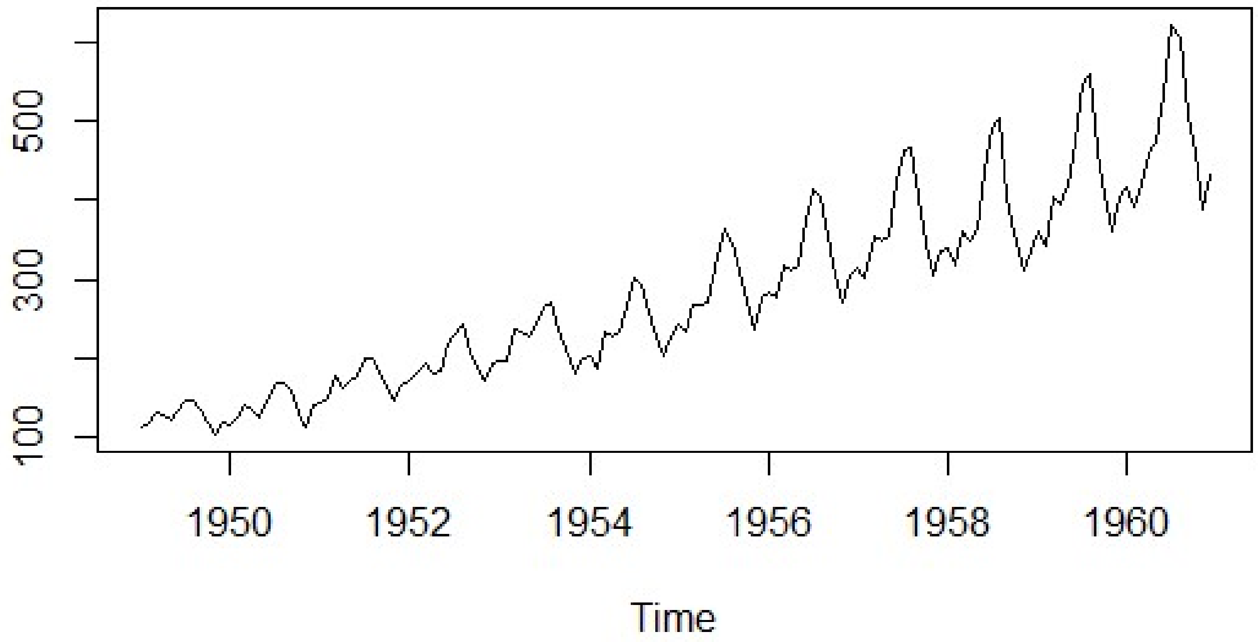
Hotel Seasonal Problem

Hotel Seasonal Problem



Hotel Seasonal Problem

- Average
- Moving Average
- Naïve Method
- Seasonal Naïve Method
- Weighted Average of the past



Exponentials Smothing

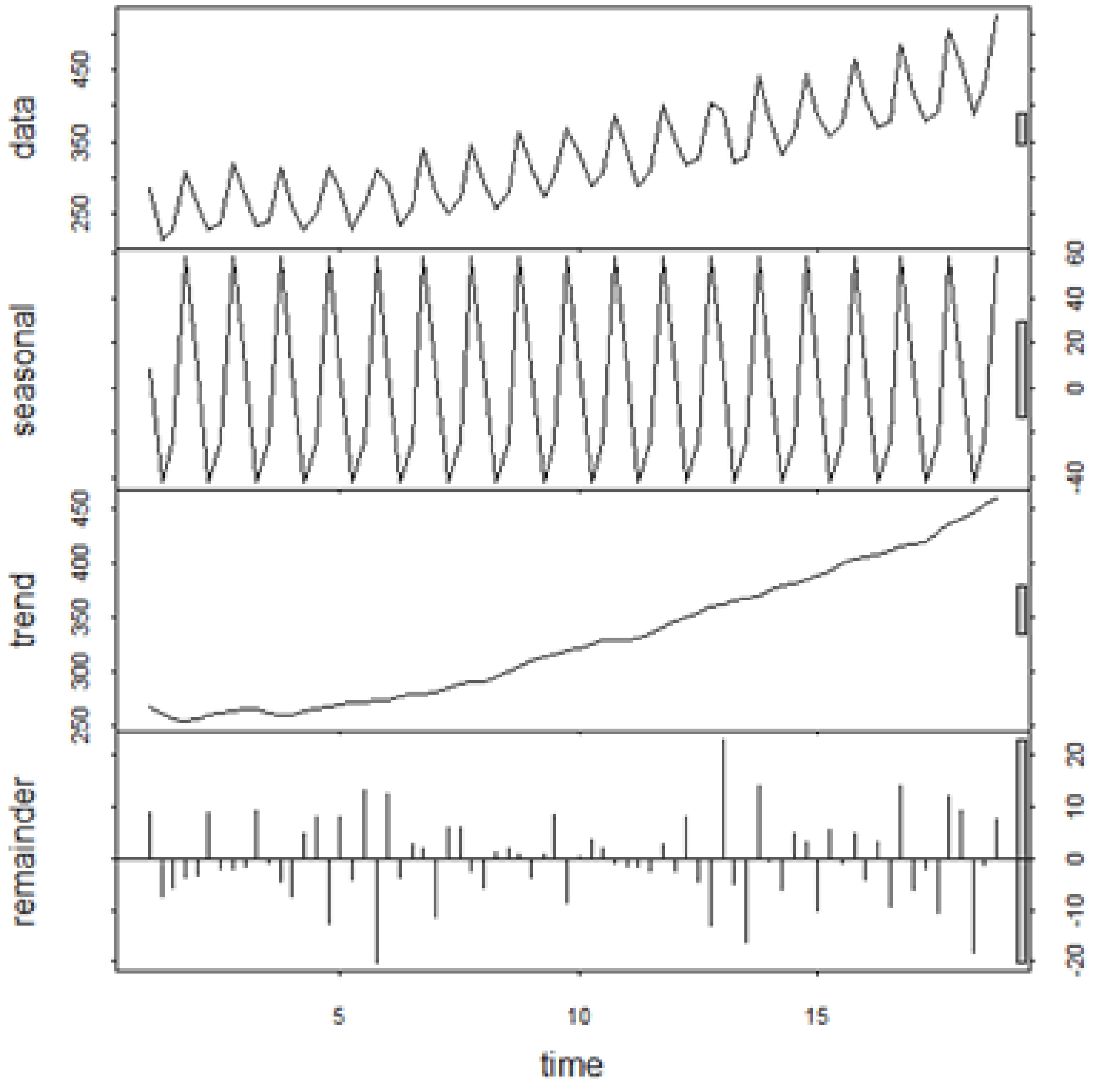
- By Taking weighted average of the past observations.
- Higher weights for recent observations.

$$\text{Forecast} = W_t\, Y_t + W_{t-1}\, Y_{t-1} + \ldots\ldots + (1-\alpha)\, n\, Y_n$$

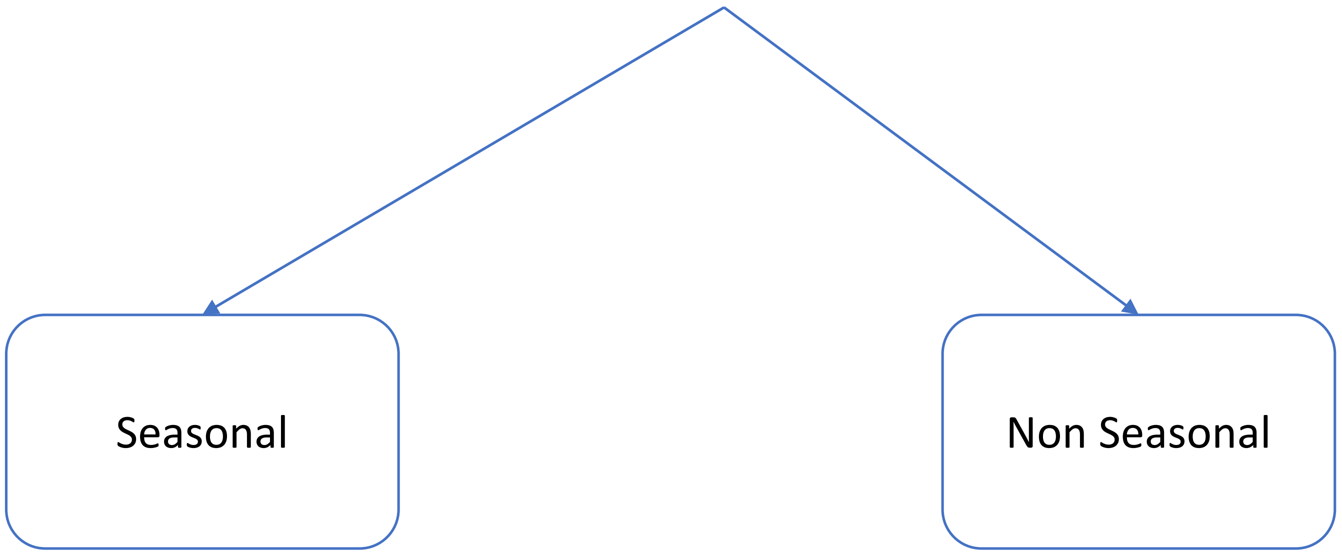
- α: smoothing parameter
- W(weight) = $\alpha(1-\alpha)$
- n: number of time periods

Time Series Decomposition

- Seasonal:
  repeating variations in the data.
- Trend:
  general tendency in the data (uptrend, downtrend).
- Remainder (error)
  difference between observed value and trend line estimate.



ARIMA (Auto Regressive Integrated Moving Average)



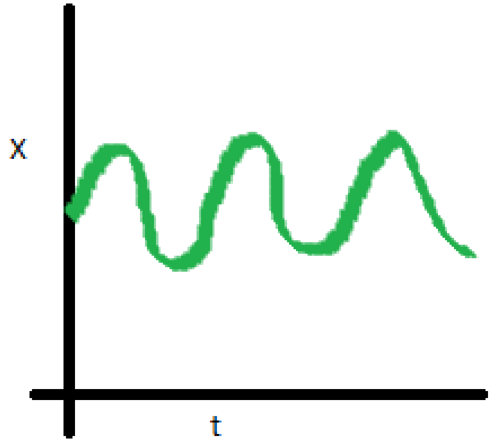
Non seasonal ARIMA

- ARIMA(p,d,q)
- It is composed of three components (AR, I, MA).
- AR: looks like liner regression with the predictor variables are previous period values.
  (p : is the number of the variables)
- MA: lag of the error component. It looks like linear model but the predictive variables are the previous periods of error.
  (q: is the number of variables)
- I (differencing): the process we use to transform a time series into a stationary one.
  (d : is the number of transformations)

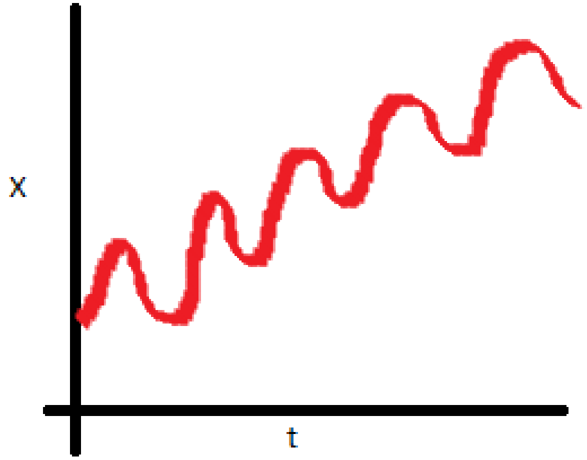
Stationary Series

- Has constant mean and variance with time.
- Easy to predict (mean, var will be the same).

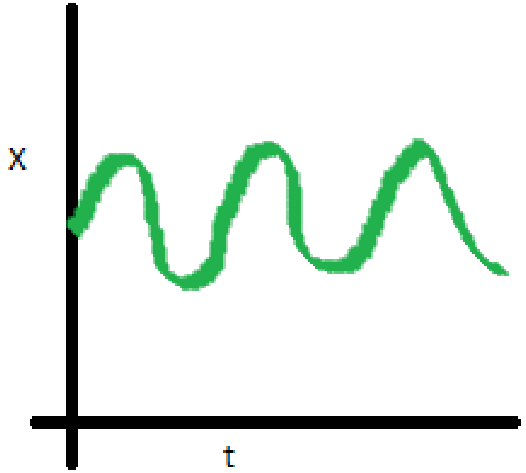
Stationary Series



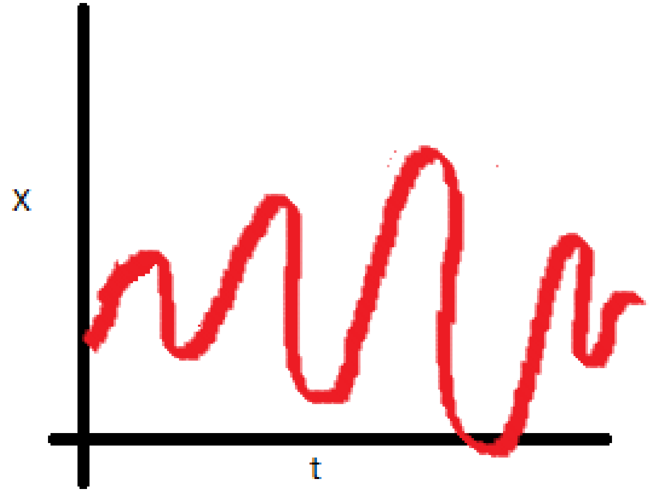
Stationary series



Non-Stationary series



Stationary series



Non-Stationary series

Transformations

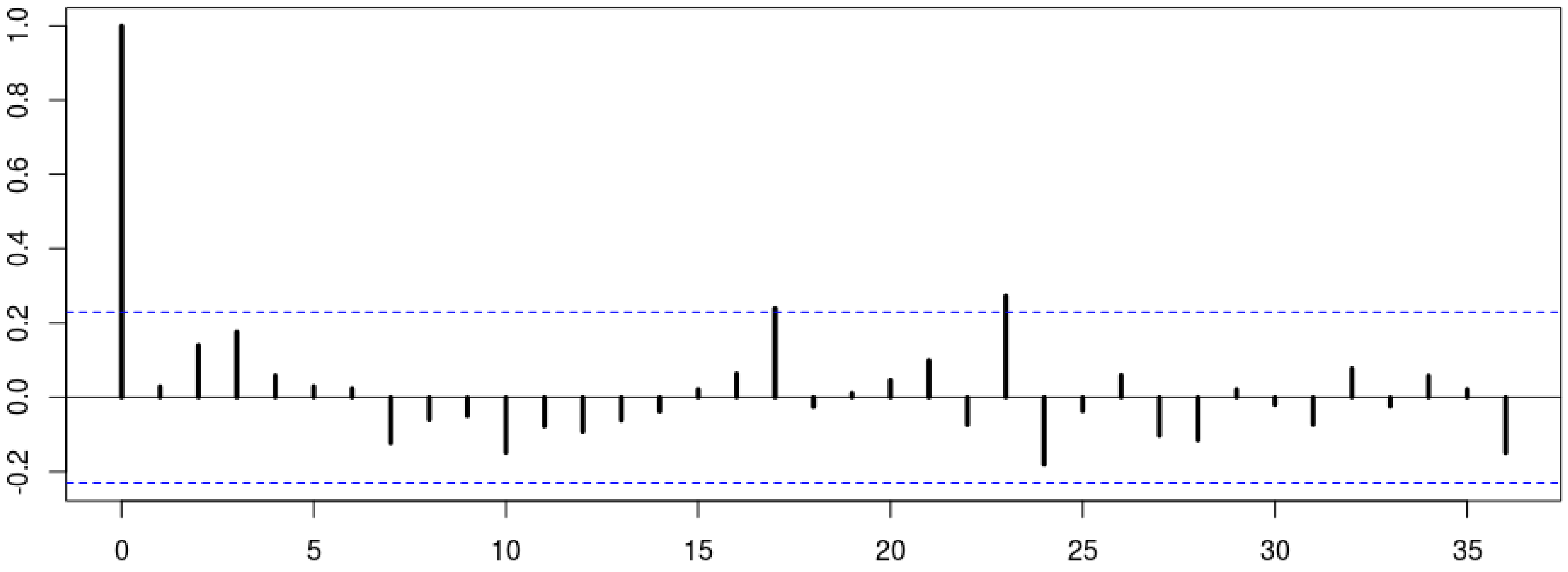
- We apply transformation to transform non stationary time series to stationary time series.

- 1st transformation
  current= current – previous period

- 2nd transformation
  current = current(from 1st transformation) – previous (from 1st transformation)

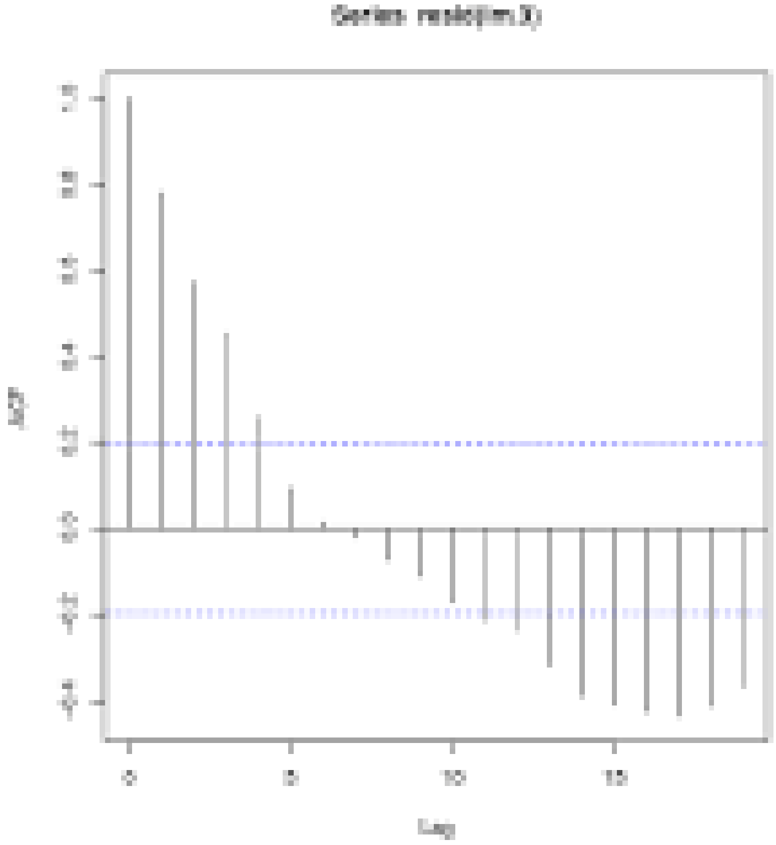
ACF (Auto Correlation Function)

- How correlated a time series is with its past values.
- ACF shows a series correlated with itself, with lag by x time units.

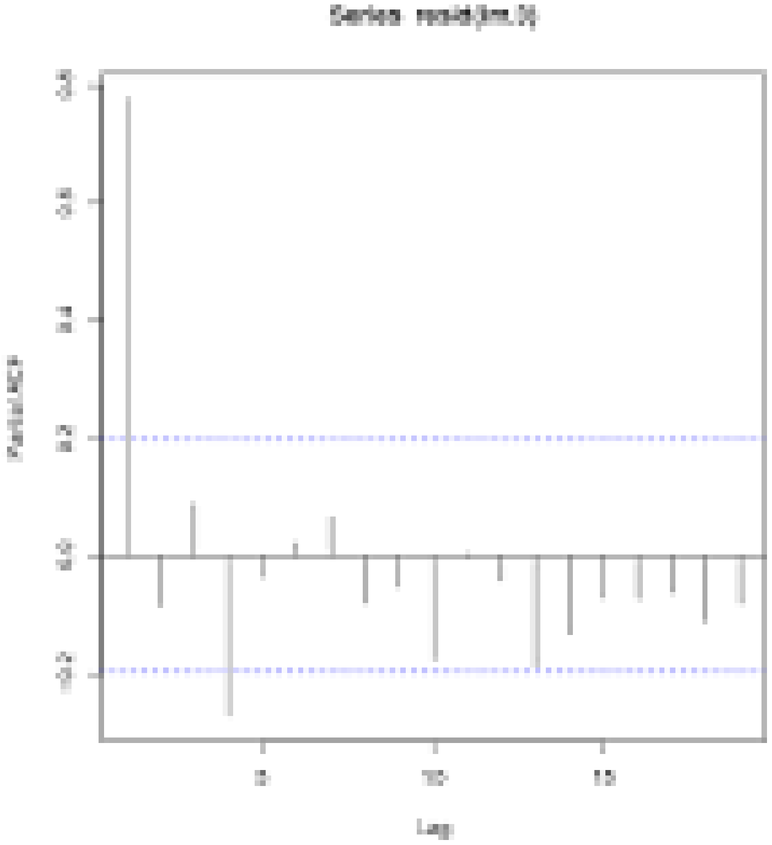


Stationary or non stationary

- Non stationary :ACF decaying smothly

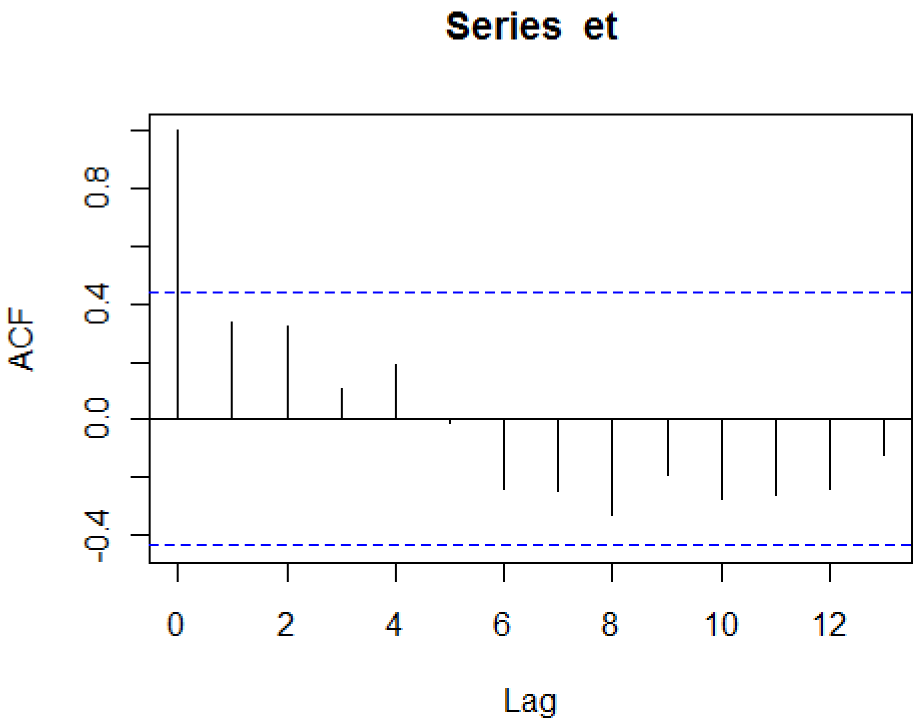


- Stationary: Recent periods are correlated

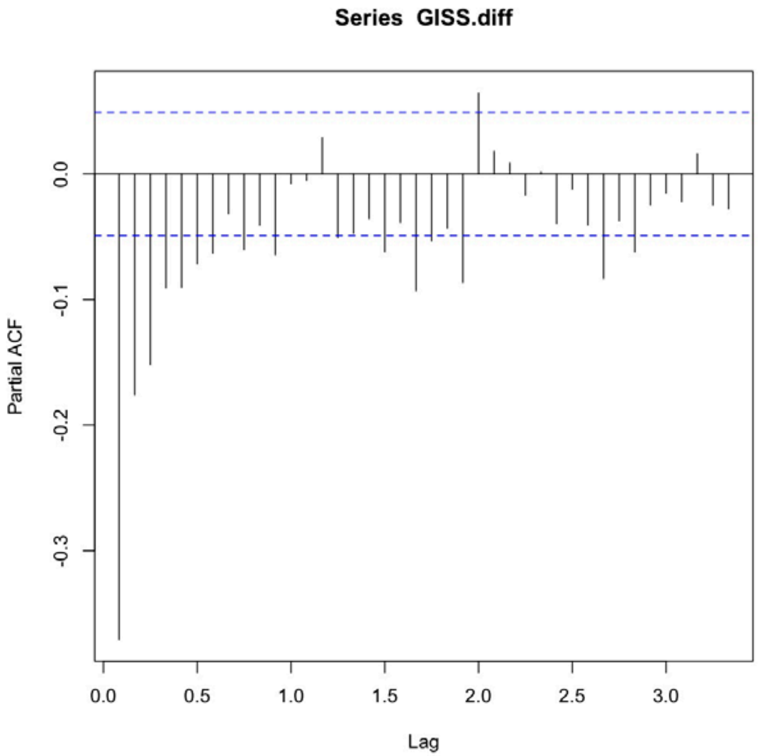


Using AR or MA or Both

- AR term is best if ACF has positive auto correlations with lag-1

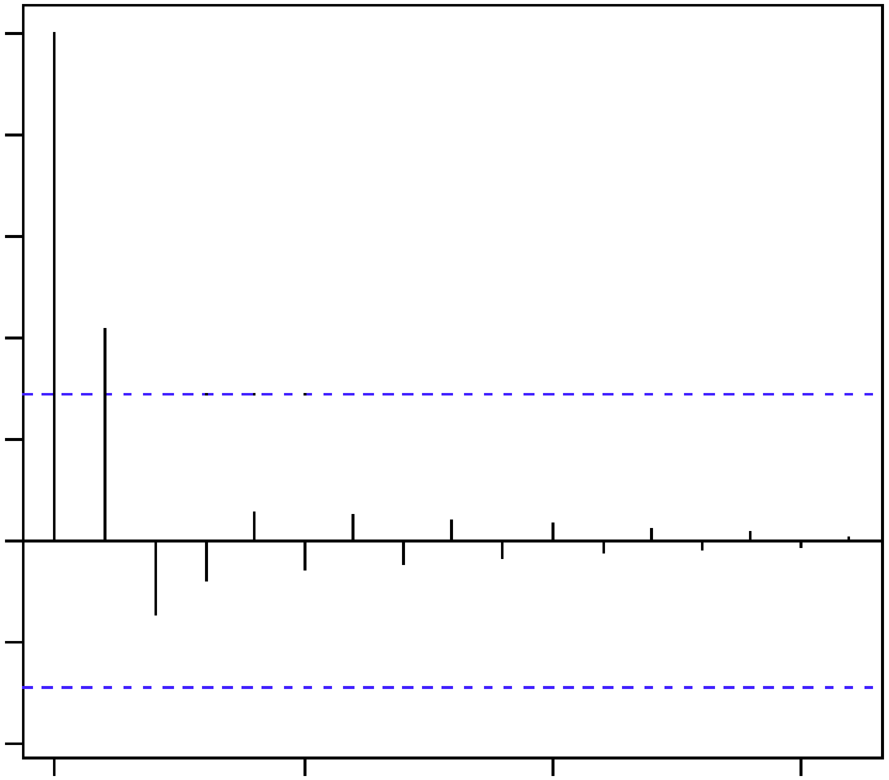


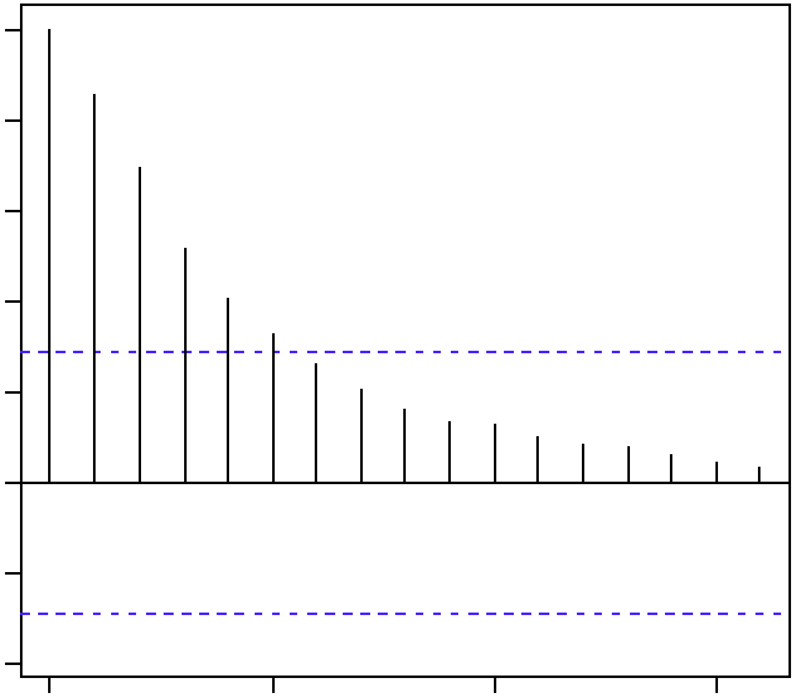
- MA term is best if ACF has negatve auto correlations with lag-1



Using AR or MA by PACF

- AR: Drops off at lag -k
- MA: Drops off gradually

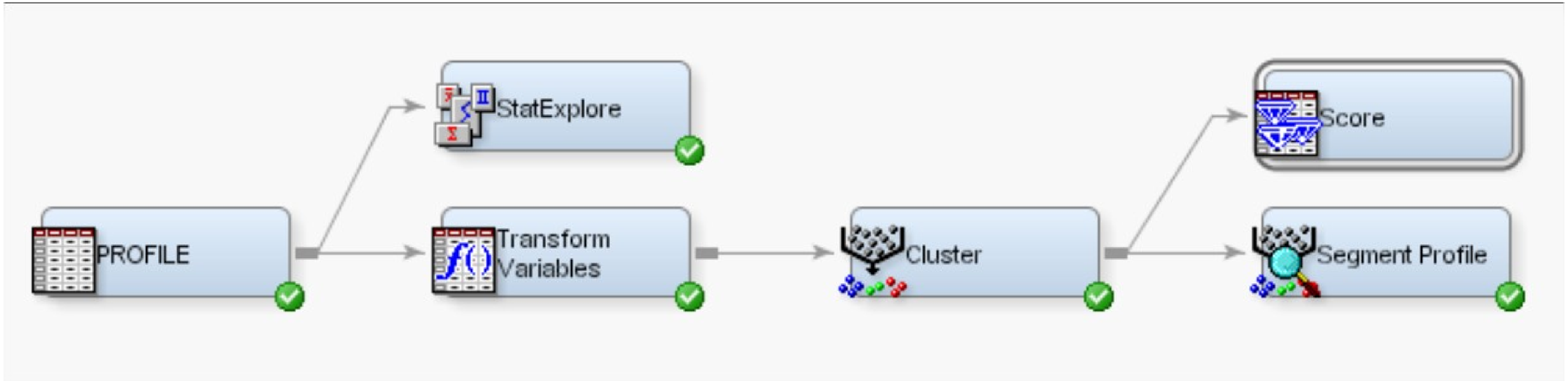




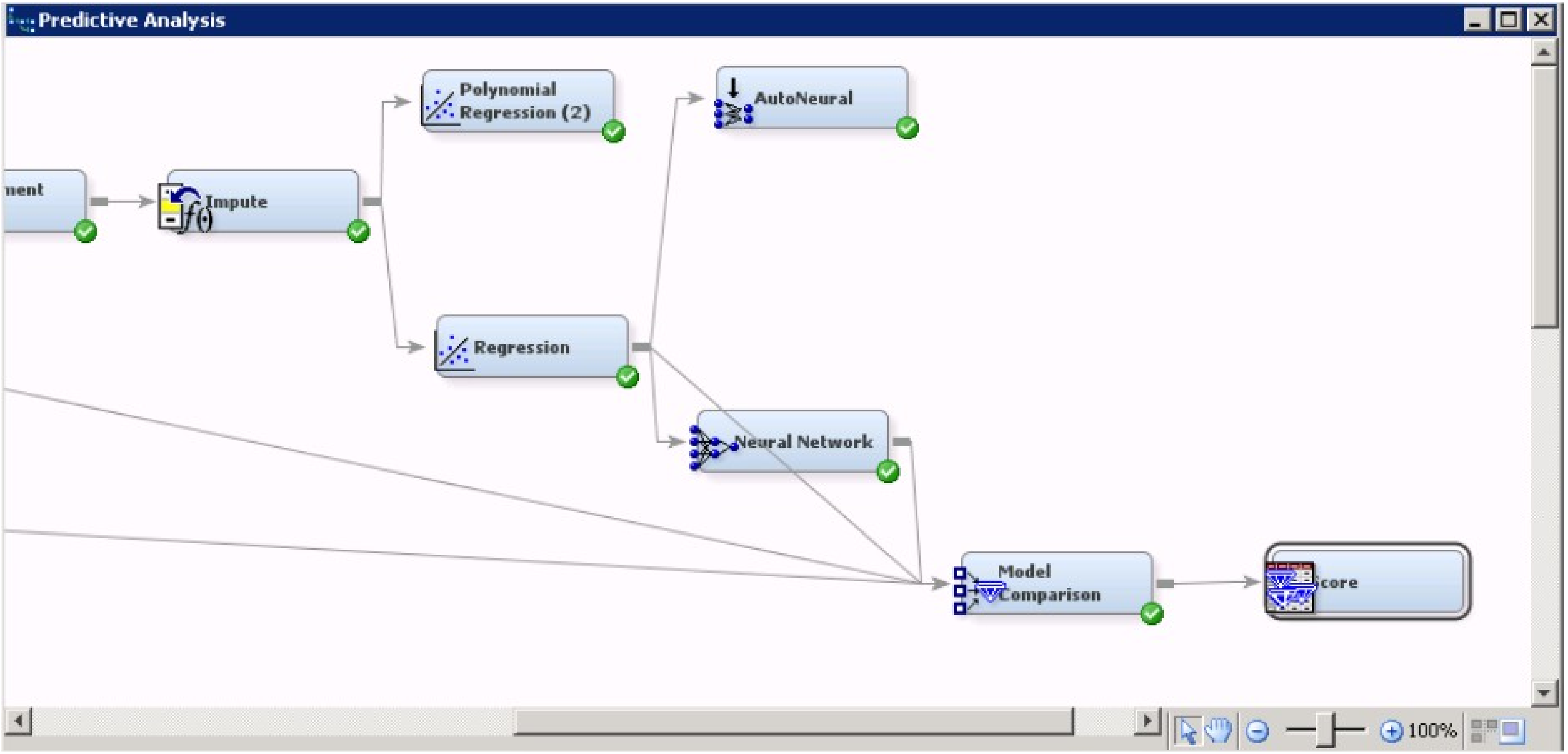
Seasonal ARIMA

- ARIMA(p,d,q)(P,D,Q)m
- m: number of period in each season
- The same previous rules but with season (e.g. 12 periods if the with monthly data).

SAS Enterprise Miner



SAS Enterprise Miner



Build the ARIMA Model

- **Step 1 - Check stationarity:** If a time series has a trend or seasonality component, it must be made stationary before we can use ARIMA to forecast. Use the *TS Plot* tool to see if the time series is stationary.
- **Step 2 - Difference:** If the time series is not stationary, it needs to be stationarized through differencing. Take the first difference, then check for stationarity. Take as many differences as it takes. Make sure you check seasonal differencing as well.
- **Step 3 - Filter out a validation sample:** This will be used to validate how accurate our model is. Use the last 6 periods as the validation sample.
- **Step 4 - Select AR and MA terms:** Use the ACF and PACF to decide whether to include an AR term(s), MA term(s), or both.
- **Step 5 - Build the model:** Build the model and set the number of periods to forecast to 6.
- **Step 6 - Validate model:** Compare the predicted values to the actuals in the validation sample.
-